Projecting future precipitation change across the semi-arid Borana lowland, southern Ethiopia (Postprint)

Authors: Mitiku A WORKU, Gudina L FEYISA, Kassahun T BEKETIE, Emmanuel GARBOLINO, Mitiku A WORKU

Date: 2023-10-17T00:00:00+00:00

Abstract

Climate change caused by past, current, and future greenhouse gas emissions has become a major concern for scientists in the field in many countries and regions of the world. This study modelled future precipitation change by downscaling a set of large-scale climate predictor variables (predictors) from the second generation Canadian Earth System Model (CanESM2) under two Representative Concentration Pathway (RCP) emission scenarios (RCP4.5 and RCP8.5) in the semi-arid Borana lowland, southern Ethiopia. The Statistical DownScaling Model (SDSM) 4.2.9 was employed to downscale and project future precipitation change in the middle (2036–2065; 2050s) and far (2066–2095; 2080s) future at the local scale. Historical precipitation observations from eight meteorological stations stretching from 1981 to 1995 and 1996 to 2005 were used for the model calibration and validation, respectively, and the time period of 1981–2018 was considered and used as the baseline period to analyze future precipitation change. The results revealed that the surface-specific humidity and the geopotential height at 500 hPa were the preferred large-scale predictors. Compared to the middle future (2050s), precipitation showed a much greater increase in the far future (2080s) under both RCP4.5 and RCP8.5 scenarios at all meteorological stations (except Teletele and Dillo stations). At Teltele station, the projected annual precipitation will decrease by 26.53% (2050s) and 39.45% (2080s) under RCP4.5 scenario, and 34.99% (2050s) and 60.62% (2080s) under RCP8.5 scenario. Seasonally, the main rainy period would shift from spring (March to May) to autumn (September to November) at Dehas, Dire, Moyale, and Teltele stations, but for Arero and Yabelo stations, spring would consistently receive more precipitation than autumn. It can be concluded that future precipitation in the semi-arid Borana lowland is predicted to differ under the two climate scenarios (RCP4.5 and RCP8.5), showing an increasing trend at most meteorological stations. This information could be helpful for policymakers to design adaptation plans in water resources management, and we suggest that the government should give more attention to improve early warning systems in drought-prone areas by providing dependable climate forecast information as early as possible.

Full Text

Preamble

Journal of Arid Land (2023) 15(9): 1023-1036
https://doi.org/10.1007/s40333-023-0063-y

Projecting Future Precipitation Change Across the Semi-arid Borana Lowland, Southern Ethiopia

Mitiku A WORKU[1]*, Gudina L FEYISA[2], Kassahun T BEKETIE[2], Emmanuel GARBOLINO[3]

[1] Department of Environment and Climate Change Management, Ethiopian Civil Service University, Addis Ababa 1000, Ethiopia
[2] Climpact Data Science, Nova-Sophia 06904, France

Abstract: Climate change caused by past, current, and future greenhouse gas emissions has become a major concern for scientists worldwide. This study modeled future precipitation change by downscaling large-scale climate predictor variables from the second generation Canadian Earth System Model (CanESM2) under two Representative Concentration Pathway (RCP) emission scenarios (RCP4.5 and RCP8.5) in the semi-arid Borana lowland, southern Ethiopia. The Statistical DownScaling Model (SDSM) 4.2.9 was employed to downscale and project future precipitation change in the middle (2036–2065; 2050s) and far (2066–2095; 2080s) future at the local scale. Historical precipitation observations from eight meteorological stations from 1981 to 1995 and 1996 to 2005 were used for model calibration and validation, respectively, with the period 1981–2018 serving as the baseline for analyzing future precipitation change. The results revealed that surface-specific humidity and geopotential height at 500 hPa were the preferred large-scale predictors. Compared to the middle future (2050s), precipitation showed a much greater increase in the far future (2080s) under both RCP4.5 and RCP8.5 scenarios at all meteorological stations (except Teltele and Dillo stations). At Teltele station, projected annual precipitation will decrease by 26.53% (2050s) and 39.45% (2080s) under RCP4.5, and by 34.99% (2050s) and 60.62% (2080s) under RCP8.5. Seasonally, the main rainy period would shift from spring (March to May) to autumn (September to November) at Dehas, Dire, Moyale, and Teltele stations, while Arero and Yabelo stations would consistently receive more precipitation in spring than in autumn. We conclude that future precipitation in the semi-arid Borana lowland is predicted to differ under the two climate scenarios, showing an increasing trend at most meteorological stations. This information could help policymakers design adaptation plans for water resources management, and we suggest that the government should improve early warning systems in drought-prone areas by providing dependable climate forecast information as early as possible.

Keywords: future precipitation; climate change; second generation Canadian Earth System Model (CanESM2); Statistical DownScaling Model (SDSM); semi-arid Borana lowland; southern Ethiopia

Citation: Mitiku A WORKU, Gudina L FEYISA, Kassahun T BEKETIE, Emmanuel GARBOLINO. 2023. Projecting future precipitation change across the semi-arid Borana lowland, southern Ethiopia. *Journal of Arid Land*, 15(9): 1023–1036. https://doi.org/10.1007/s40333-023-0063-y

Introduction

Strong evidence suggests that global climate is changing mainly due to increasing concentrations of greenhouse gases in the atmosphere from various human activities (Intergovernmental Panel on Climate Change (IPCC), 2014, 2022). The global average temperature showed a warming trend of 0.85°C from 1880 to 2012 (IPCC, 2013; Birara et al., 2018). Moreover, the Fifth Assessment Report of IPCC (IPCC AR5) mentioned that observations—including increases in global average land and sea temperatures, widespread melting of snow and ice, and rising sea levels—indicate further warming of the climate system (IPCC, 2014).

Human-induced climate change, including more frequent and intense extreme events, has widespread adverse impacts and has caused related losses and damages to the physical environment and humans beyond natural climate variation. Increases in weather and climate extremes have led to some irreversible impacts as natural and human systems are pushed beyond their adaptive capacity (IPCC, 2022). The vulnerability of ecosystems and humans to climate change differs substantially among climatic regions, communities, and countries, attributable to socio-economic, cultural, political, governance, and geographical factors (Gumucio et al., 2020; IPCC, 2022).

Climate change caused by past, current, and future greenhouse gas emissions has various adverse impacts on the physical environment and socio-economic development of nations (IPCC, 2022), making it a major concern for scientists in the field (Mekonnen and Berlie, 2020; Bulti et al., 2021). Several studies have demonstrated future increases in the intensity and frequency of extreme events (particularly floods and droughts) until the end of this century in many regions, including Ethiopia (IPCC, 2014; Nasim et al., 2016; Mubeen et al., 2020). Hence, prior information on future climate is crucial for identifying potential associated risks at an early stage and supporting the planning and implementation of intervention measures, including adaptation and mitigation responses, to cope with increasing extreme events.

Future climate information can be projected from Global Circulation Models (GCMs), which are readily available from different sources but at coarser resolution (Deb et al., 2018; Bulti et al., 2021). However, local-scale climate studies demand climate information at high resolution (fine-scale) (Pervez and Henebry, 2014), leading to the development of downscaling methods. Among existing downscaling methods, statistical downscaling—which assumes an empirical relationship between large-scale climatic variables (predictors) and local-scale variables (predictands)—has been widely adopted (Wilby et al., 2002; Wilby and Dawson, 2013). Despite its limitations, statistical downscaling can provide first-hand information about future climate conditions.

Arid and semi-arid areas in the Sahel region and the Horn of Africa are often identified as the most vulnerable regions, where pastoralists, fishing communities, and small-holder farmers are adversely impacted by current and future climate (Ayanlade and Ojebisi, 2019; Muringai et al., 2019; Mogomotsi et al., 2020; IPCC, 2022). Climate change has already negatively impacted crop production by altering precipitation patterns and distribution (Sultan et al., 2019) and has reduced total agricultural productivity growth by 34% in Africa since 1961 (Ortiz-Bobea et al., 2021). Impacts of global climate on food availability are expected to lead to higher food prices and greater risk of hunger for people in African countries, including the semi-arid lowlands of Ethiopia (IPCC, 2022). Previous research on projecting future climate change at the local scale by downscaling GCMs (Hussain et al., 2017; Matthew and Abiye, 2017; Hasan and Nile, 2020; Mohammed et al., 2020; Bulti et al., 2021; Javaherian et al., 2021; Seng et al., 2021; Shahriar et al., 2021; Tarekegn et al., 2021; Munawar et al., 2022) was conducted either in highland regions where precipitation is not scarce or at larger spatial scales, making local-scale climate analysis still challenging. Thus, studying precipitation change at the station or district scale helps identify areas with limited precipitation conditions and provides information to suggest better management practices.

From this perspective, we chose the semi-arid Borana lowland—one of the semi-arid regions frequently hit by extreme climate conditions in Ethiopia, particularly drought—as a case study. There is a need to obtain prior climate information in this region to help manage drought-related risks through various mechanisms. Additionally, studies on future precipitation change in the semi-arid Borana lowland can provide supporting information to decision-makers, local institutions, and inhabitants engaged in climate-sensitive sectors such as livestock systems and small-holder farming. Accordingly, we projected future precipitation change in the middle future (2036–2065; 2050s) and far future (2066–2095; 2080s) through downscaling of CanESM2 GCM data under two Representative Concentration Pathway (RCP) emission scenarios (RCP4.5 and RCP8.5) in the semi-arid Borana lowland of southern Ethiopia. The research findings will help formulate better measures for water resources management and reduce the adverse effects of climate-related risks in the locality.

2.1 Study Area

The semi-arid Borana lowland (103°03 -103°05 E, 03°30 -05°38 N; 450-2487 m a.s.l.) is located in the southern part of Ethiopia [Figure 1: see original paper]. The annual mean temperature varies between 28°C and 33°C with little seasonal variation (Fenetahun et al., 2022), and mean annual precipitation was estimated between 350 and 900 mm by Debela et al. (2019) and between 285 and 741 mm by Worku et al. (2022). Precipitation with high spatial and temporal fluctuations falls mainly during two periods: spring (from March to May) and autumn (from September to November), which account for nearly 60% and 27% of annual precipitation, respectively (Gemedo et al., 2006).

There are two dry seasons in the study area: the long dry spell in winter (from December to February of the next year) and the short dry spell in summer (from June to August) (Korecha and Barnston, 2007). The seasonal characteristics, pattern, and distribution of precipitation in the study area are unique and differ from other regions in Ethiopia. In summer, when most regions of Ethiopia receive rain, the semi-arid Borana lowland remains dry due to its rain-shadow location.

Fig. 1 Overview of the semi-arid Borana lowland based on digital elevation model (DEM) data. The DEM data were downloaded from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Archive–Shuttle Radar Topographic Mission (SRTM) with a spatial resolution of 1 arc-second (https://www.usgs.gov).

2.2.1 Meteorological Data

Historical daily precipitation observations from 1981 to 2018 at all meteorological stations in the study area [Figure 1: see original paper] were collected from the Ethiopian Meteorological Institute (EMI) (https://www.ethiomet.gov.et). Since meteorological station observations are not free from missing values, gridded precipitation data with a spatial resolution of 4 km$×$4 km were used to complete the data. The gridded precipitation data used in this study are a product of the Enhancing National Climate Services (ENACTS) initiative that integrates meteorological station observations with freely available high-resolution global products using Climate Data Tool (CDT) (https://iri.columbia.edu/resources/enacts/).

2.2.2 CanESM2 GCM

The CanESM2 GCM was developed by the Canadian Centre for Climate Modelling and Analysis (CCCma) and is freely available online (https://www.climate-scenarios.canada.ca). It is a comprehensive earth system model that includes coupled atmosphere, ocean, sea-ice, and terrestrial and ocean carbon components (Arora et al., 2011; Virgin et al., 2021; Jeong et al., 2022), with a resolution of 2.8125° latitude$×$2.8125° longitude (Arora et al., 2011). CanESM2 GCM has been widely applied in Ethiopia (Dile et al., 2013;

Deb et al., 2018; Bulti et al., 2021; Tarekegn et al., 2021) and other tropical regions (Javaherian et al., 2021; Seng et al., 2021; Shahriar et al., 2021; Lachgar et al., 2022).

The particular ensemble used in the CanESM2 GCM is the first member team where the past climate condition over the period 1961-2005 is represented by historical simulation. Projections for future climate are based on scenarios in the IPCC AR5, with the projected time period from 2006 to 2100. We downloaded 26 climate variables from the CanESM2 GCM data for both the historical period (1961-2005) and future period (2006-2100) under RCP4.5 and RCP8.5 scenarios. These data were ready to be used as inputs in the statistical downscaling models to obtain the downscaled future precipitation data for the semi-arid Borana lowland.

2.2.3 National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis Dataset

The reanalysis dataset for large-scale climate variables during 1961-2005 was obtained from NCEP/NCAR with a horizontal resolution of 2.5000° latitude$×$2.5000° longitude (Goyal and Ojha, 2012). The NCEP/NCAR dataset was used for calibration and validation of the downscaling model. We chose grid data falling in BOX_{{{015X}}_{{34Y}}} (where 015 is the longitudinal index and 34 is the latitudinal index) and interpolated them to adjust the resolution to match the CanESM2 GCM data. All climate variables were normalized using the following equation (Hassan et al., 2014; Bulti et al., 2021; Shahriar et al., 2021):

where $\hat{u}$ is the normalized value for the climate variable at time t; u_t is the original value for the climate variable at time t; $\bar{u}$ is the multi-year average value for the climate variable over the period; and σ_u is the standard deviation.

2.3.1 Model Setup

The SDSM is a regression-based hybrid model that combines stochastic weather generation and multiple linear regression (MLR) for generating future emission scenarios (Wilby et al., 2002). In this study, we used SDSM 4.2.9 to downscale and project future precipitation. SDSM first calculates the relationship between large-scale predictors and local-scale predictands to develop future climate conditions. There are two sub-models in SDSM: conditional and unconditional processes, where the conditional sub-model is used for precipitation projection since it is dependent on other factors (i.e., predictors) (Wilby et al., 2002). SDSM is performed through steps including screening of predictors, calibration and validation of the model, and generation of climate scenarios. The model structure is described in Figure 2 [Figure 2: see original paper] (Wilby et al., 2002; Hasan and Nile, 2020; Shahriar et al., 2021).

Fig. 2 Statistical DownScaling Model (SDSM) structure used in this study. CanESM2, second generation Canadian Earth System Model; NCEP/NCAR, National Center for Environmental Prediction/National Center for Atmospheric Research; RCP, Representative Concentration Pathway. r represents the correlation coefficient, and P represents the statistical significance.

2.3.2 Selection of Appropriate Large-Scale Predictors

Appropriate selection of large-scale climate variables (termed predictors) is crucial in projecting future precipitation, as it highly affects future climate scenarios (Hassan and Nile, 2020). Predictor screening was adopted using different approaches, including correlation coefficient matrix results, partial correlation, scatter plots, and P-value among observed precipitation and NCEP/NCAR predictors. A relatively high correlation coefficient ($r > 0.6$) and low P-value ($P < 0.05$) were used to select the best predictors (Yang et al., 2017; Ozbuldu and Irvem, 2021). The entire NCEP/NCAR predictors are given in Table 1 .

Table 1 List of the large-scale predictors in the NCEP/NCAR reanalysis dataset and CanESM2 GCM

Predictor	Description	Predictor	Description
mslp	Mean sea level pressure	p1_u	Geostrophic air flow velocity at surface
p1_f	Zonal velocity component at surface	p1_v	Meridional velocity component at surface
p1_z	Vorticity at surface	p1_{zh}	Divergence at surface
p5_u	Geostrophic air flow velocity at 500 hPa	p5_f	Zonal velocity component at 500 hPa
p5_v	Meridional velocity component at 500 hPa	p5_z	Vorticity at 500 hPa
p5_{zg}	Geopotential height at 500 hPa	p5th	Wind direction at 500 hPa
p5_{zh}	Divergence at 500 hPa	p8_u	Geostrophic air flow velocity at 850 hPa
p8_f	Zonal velocity component at 850 hPa	p8_v	Meridional velocity component at 850 hPa
p8_z	Vorticity at 850 hPa	p8_{zg}	850 hPa geopotential height
p8th	Wind direction at 850 hPa	p8_{zh}	Divergence at 850 hPa

Predictor	Description	Predictor	Description
ppr	Total precipitation	p5shum	Specific humidity at 500 hPa
p8shum	Specific humidity at 850 hPa	shum	Surface-specific humidity
temp	Mean temperature at 2 m		

Note: NCEP/NCAR, National Center for Environmental Prediction/National Center for Atmospheric Research; CanESM2, second generation Canadian Earth System Model; GCM, Global Circulation Model.

2.3.3 Calibration and Validation of the SDSM

Following selection of the large-scale predictors, the final ones were used in SDSM calibration. A multiple regression equation with optimization techniques using the ordinary least squares (OLS) method was employed to derive the relationship between large-scale predictors and local-scale predictands (Shahriar et al., 2021). Based on available historical daily precipitation observations (1981-2018), we classified the data into two sets: precipitation observations from 1981 to 1995 for SDSM calibration, and from 1996 to 2005 for SDSM validation.

Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE) using the following equations (Hu et al., 2016; Mathew and Abiye, 2017; Habib ur Rahman et al., 2018; Mubeen et al., 2020; Javaherian et al., 2021):

$$R^2 = \frac{\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

where P_i is the projected daily precipitation (mm); O_i is the observed daily precipitation (mm); $\bar{P}$ and $\bar{O}$ are the average of projected daily precipitation (mm) and average of observed daily precipitation (mm), respectively; and n represents the total number of data. The closer the R^2 value is to 1 and the RMSE value is to 0, the better the projection for future precipitation will be (Ghorbani et al., 2018). The calibrated and validated results are provided in Table 2 .

Table 2 Statistical indices for the calibration and validation of the SDSM

Station	Calibration period (1981-1995)	Validation period (1996-2005)
	R^2	RMSE
Arero		
Dehas		
Dillo		
Moyale		
Teltele		
Yabelo		

Note: SDSM, Statistical DownScaling Model; R^2, coefficient of determination; RMSE, root mean square error.

2.3.4 Bias Correction

To remove errors in downscaled precipitation, bias correction is necessary (Wilby and Dawson, 2013; Hussain et al., 2017; Shahriar et al., 2021). We adopted the delta method to eliminate overestimation and/or underestimation of model outputs from the daily time series of downscaled precipitation. The equation is given by Dessu and Melesse (2013):

$$P_{\text{deb}} = P_{\text{scen (daily)}} \times \frac{\bar{P}_{\text{obs (monthly)}}}{\bar{P}_{\text{cont (monthly)}}}$$

where P_{deb} is the de-biased (corrected) daily precipitation (mm) for future time period; $P_{\text{scen (daily)}}$ is the daily precipitation generated by SDSM for the future time period (mm); $\bar{P}_{\text{cont (monthly)}}$ is the mean monthly precipitation for the baseline period (1981-2018) simulated by SDSM (mm); and $\bar{P}_{\text{obs (monthly)}}$ represents the mean monthly precipitation observed in the baseline period (1981-2018) (mm). The time period 1981-2018 was considered and used as the baseline period to analyze future precipitation change in the study area.

2.3.5 Generation of Future Climate Scenarios

After bias correction, future climate scenarios were generated for the middle (2050s) and far (2080s) future. Among the four emission scenarios (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) developed by CanESM2 (Moss et al., 2010; Meinshausen et al., 2011; van Vuuren et al., 2011; IPCC, 2013), the RCP4.5 scenario (characterized by limited mitigation practices with radiative forcing of 4.5 W/m^2 by 2100) and RCP8.5 scenario (with no mitigation practices implemented, ultimately resulting in radiative forcing of 8.5 W/m^2 by 2100) were considered. The RCP2.6 scenario is a 'peak-and-decline' scenario leading to very low greenhouse gas concentration levels whereby radiative forcing reaches 3.0 W/m^2 by 2050 and returns to 2.6 W/m^2 by 2100 (van Vuuren et al., 2011). Due to its stringent mitigation strategy, RCP2.6 was overlooked. Additionally, the RCP6.0 scenario, which falls between limited and no mitigation strategies, was not considered.

3.1 Selection of Appropriate Large-Scale Predictors

The NCEP/NCAR predictors were evaluated using correlation coefficient and P-value. Surface-specific humidity presented the most important large-scale predictor for the predictand (precipitation), followed by geopotential height at 500 hPa (Table 3). Additionally, geopotential height at 850 hPa projected local-scale precipitation well at three meteorological stations, while both geostrophic air flow velocity at 850 hPa and mean temperature at 2 m projected local-scale precipitation well at two meteorological stations (Table 3).

Table 3 NCEP/NCAR predictors screened to downscale precipitation in the SDSM

Station	Predictand	Predictor
Arero	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa, Geostrophic air flow velocity at 850 hPa
Dehas	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa, Geopotential height at 850 hPa
Dillo	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa
Moyale	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa, Mean temperature at 2 m
Teltele	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa, Geopotential height at 850 hPa
Yabelo	Precipitation	Surface-specific humidity, Geopotential height at 500 hPa, Mean temperature at 2 m

Note: √ indicates the selected large-scale predictor for precipitation at the corresponding meteorological station.

3.2 Projected Monthly Precipitation Under RCP Scenarios

At Arero station, projected monthly precipitation values were higher than monthly precipitation observations in the baseline period (1981–2018) (historical observations) [Figure 3: see original paper]. Specifically, RCP4.5 projected higher precipitation than RCP8.5 in the 2080s in November, October, and April, with projected precipitation values in the 2080s appearing higher than those in the 2050s.

At Dehas station, projected precipitation values under RCP4.5 in the 2050s during the main rainy season (March to May) were more or less equal to historical observations, whereas in the short rainy season (September to November), projected precipitation values under both scenarios were higher than historical observations, particularly in October and November. At Dillo station, monthly projected precipitation values were close to monthly historical observations, making it the driest station historically as revealed by model outputs.

At Dire station, projected monthly precipitation values in the future were lower than historical observations only in March and April. Both RCP4.5 and RCP8.5 projected higher precipitation totals in the middle and far future during the short rainy season than during the main rainy season. The projected monthly precipitation also identified precipitation occurrence in June. During all months except October and November, similar precipitation conditions were observed between projected values under both scenarios and historical observations, with historical observations slightly lower than projected ones.

At Moyale station, projected monthly precipitation values were higher than monthly historical observations for all months except July under RCP8.5 in the far future. Both scenarios projected higher monthly precipitation in October, November, and April, with values reaching 370, 210, and 165 mm under RCP8.5. It appears the main rainy season would shift from spring to autumn at most meteorological stations in the future. Projected monthly precipitation values seemed lower than historical observations from March to May at Teltele station; however, both scenarios simulated similar precipitation conditions except for RCP8.5 in the far future (2080s). Moreover, projected monthly precipitation revealed drier conditions at Teltele station with no precipitation occurrence from June to August.

At Yabelo station, projected monthly precipitation values were lower than monthly historical observations only in March and September. Furthermore, projected monthly precipitation values during the main rainy season were higher than those during the short rainy season under both scenarios.

3.3 Projected Seasonal Precipitation Under RCP Scenarios

The study area receives most of its precipitation in spring, which is supposed to be the main rainy season, followed by autumn as the short rainy season. As shown in Figure 4 [Figure 4: see original paper], the model projected that spring and summer would receive more precipitation than autumn in the middle and far future at Arero station. Projected seasonal results revealed more precipitation would occur in autumn at Dehas, Dire, Moyale, and Teltele stations. At Teltele station particularly, projected seasonal precipitation fell below historical observations, whereas it showed some similarity with historical observations at Yabelo station, where more precipitation would occur in spring followed by autumn.

At more than half of the studied meteorological stations, precipitation received in autumn was higher than that in spring. Overall, it can be summarized that in the future (both middle and far future), there will be a shift in the main rainy season from spring to autumn, meaning precipitation in autumn will exceed that in spring, exerting greater impact on socio-economic activities in the study area.

3.4 Projected Annual Precipitation Under RCP Scenarios

Projected annual precipitation values under both scenarios in the future (middle and far future) were compared to precipitation observations in the baseline period (1981-2018) for all meteorological stations (Table 4). Results revealed both RCP4.5 and RCP8.5 projected a huge increase in annual precipitation in the far future (2080s) compared to the middle future (2050s), with significant disparity among stations, where Arero, Dire, and Moyale exhibited higher increases.

At Teltele station, projected annual precipitation values were lower than historical observations, with decreases of 26.53% (2050s) and 39.45% (2080s) under RCP4.5, and 34.99% (2050s) and 60.62% (2080s) under RCP8.5. Hence, drier conditions will occur at this station. Similar results appeared at Dillo station, with decreases of 2.26% (RCP4.5) and 1.07% (RCP8.5) in the middle future (2050s).

Conversely, projected annual precipitation exhibited increases of 13.42% (Miyo station) and 119.76% (Moyale station) under RCP4.5 in the middle future, and 0.80% (Dillo station) and 154.65% (Dire station) under RCP4.5 in the far future. Under RCP8.5, percentage changes ranged from 2.10% (Yabelo station) to 150.62% (Moyale station) and from 3.20% (Dillo station) to 200.69% (Dire station) in the middle and far future, respectively. Accordingly, Moyale and Dire stations will experience significant increases in annual precipitation compared to other stations.

Discussion

The large-scale predictors of surface-specific humidity and geopotential height at 500 hPa projected local-scale precipitation well at seven and five of the eight meteorological stations, respectively. Similarly, Bulti et al. (2021) found that surface-specific humidity is one of the super predictors of CanESM2 in analyzing future extreme precipitation in Adama, Ethiopia. Conversely, total precipitation was reported as the super predictor at Kuching, Bintulu, and Limbang stations, while geopotential height at 500 hPa projected minimum temperature well at Bintulu and Limbang stations in Chittagong Division, Bangladesh (Hussain et al., 2017).

According to Matthew and Abiye (2017), mean sea level pressure, geostrophic air flow velocity at surface, surface-specific humidity, and specific humidity at 500 hPa were the most sensitive large-scale predictors for projecting future local-scale precipitation over Nigeria. The selection of large-scale predictors in this study was mostly similar to procedures applied in Hashmi et al. (2011), Hassan et al. (2014), and Hussain et al. (2017).

The study area has been one of the driest regions in Ethiopia in winter and summer. This situation is consistent with future projections, as the model projected drier conditions at Dehas, Dillo, Dire, Miyo, and Teltele stations. Months from December to February are getting drier across the whole country due to invasion of dry continental winds from Asian landmasses and northern Africa. The influence of these winds will be sustained even in the future and become responsible for extended dryness in this region. However, during June to August, most parts of the country will receive more precipitation except the study area and northeastern lowlands of Ethiopia, attributable to their rain-shadow locations in summer. Similar conditions were projected under RCP4.5 and RCP8.5 scenarios in the middle (2050s) and far (2080s) future.

Precipitation from March to May was projected to decrease in the future in the study area, particularly at Dillo, Miyo, and Teltele stations, whereas more precipitation will occur in October and November than in other months at Dehas, Dire, and Moyale stations. Therefore, distribution of projected monthly precipitation will not be consistent over the semi-arid Borana lowland. According to Tarekegn et al. (2022), simulated monthly precipitation exhibited a decreasing trend in all months in the 2050s and 2080s, with the highest decrease (97.00%) under RCP8.5 in the 2050s. Additionally, Mohammed et al. (2020) found decreases in future precipitation in February, April, and June under both RCP4.5 and RCP8.5 scenarios, with the highest decrease projected in February in the 2080s (45.00% and 43.40% under RCP4.5 and RCP8.5, respectively) in the Rift Valley Basin, Ethiopia.

In this study, projected seasonal precipitation was not consistent across meteorological stations in the Borana lowland. Except for Arero station, summer was projected to be the driest season under both RCP4.5 and RCP8.5 scenarios. This was supported by Javaherian et al. (2021), who reported the lowest precipitation in summer at Lar Dam, Iran. At Dehas, Dire, Miyo, Moyale, and Teltele stations, higher precipitation in the future was projected in autumn, similar to results obtained by Javaherian et al. (2021). Some stations, including Arero, Dillo, and Yabelo, would receive more precipitation in spring, consistent with Mohammed et al. (2020), who found future precipitation will increase by 16.00% (RCP4.5) and 20.00% (RCP8.5) in spring in the 2080s. Dile et al. (2013) also found increasing trends of spring precipitation in the 2050s and 2080s in the Gilgel Abay River Basin, Ethiopia. Winter followed by summer will be drier seasons across the study area. As reported by Mohammed et al. (2020), future precipitation in winter will decrease by 1.80% under RCP4.5 in the 2050s. Similarly, Lachgar et al. (2022) noticed reductions in future precipitation in winter and summer over Casablanca City, Morocco.

Annual precipitation was projected to increase in the future at most meteorological stations except Teltele and Dillo, which exhibited reductions. These results are consistent with research conducted in Tikur Wuha, Adama City, central Ethiopia (Mohammed et al., 2020; Bulti et al., 2021) and Bilate Watershed, Ethiopian Rift Valley Basin (Tekle, 2015). Mohammed et al. (2020) predicted increases in future precipitation by 15.40% (RCP4.5) and 17.40% (RCP8.5) in the 2050s, as well as 16.00% (RCP4.5) and 19.44% (RCP8.5) in the 2080s. Conversely, Tarekegn et al. (2022) found a reduction in mean annual precipitation of about 22.50% in the 2080s, with reductions under Special Report on Emission Scenarios (SRES; A2 and B2 scenarios) greater than under RCP scenarios (RCP4.5 and RCP8.5). Decreases in annual precipitation of 20.00%–30.00% under RCP4.5 and about 20.00%–40.00% under RCP8.5 were also projected in the Casablanca-Settat region of Morocco during 2036–2100 (Lachgar et al., 2022).

Conclusions

In this study, we projected future precipitation in the semi-arid Borana lowland of southern Ethiopia under RCP4.5 and RCP8.5 scenarios using SDSM. We downscaled CanESM2 GCM data for the middle (2050s) and far (2080s) future and projected future precipitation at monthly, seasonal, and annual scales.

Based on partial correlation, scatter plots, and P-value, surface-specific humidity and geopotential height at 500 hPa were screened as the most prominent predictors among the 26 NCEP/NCAR large-scale predictors for precipitation. Both RCP4.5 and RCP8.5 projected huge increases in annual precipitation in the far future (2080s) compared to the middle future (2050s), with significant disparity among stations, where Arero, Dire, and Moyale exhibited higher increases. Conversely, at Teltele station, projected annual precipitation will decrease by 26.53% (2050s) and 39.45% (2080s) under RCP4.5, and by 34.99% (2050s) and 60.62% (2080s) under RCP8.5. Increases in projected annual precipitation are expected for most stations except Teltele and Dillo. Seasonally, projected precipitation would be higher in autumn than spring at Dehas, Dire, Moyale, and Teltele stations, with a shift of the main rainy season from spring to autumn at these stations. Spring would remain the main rainy season at Arero and Yabelo stations. Increases in projected monthly precipitation will be greater in April, March, October, and November than in other months.

In general, future precipitation in the semi-arid Borana lowland will change considerably under RCP4.5 and RCP8.5 scenarios. This study can inform policymakers preparing readiness plans and formulating better measures to reduce climate-related risks. Climate modeling is not free from uncertainties, and further downscaling research involving multi-GCM ensembles and downscaling approaches could reduce these uncertainties and produce better performance.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgements: The authors thank the Ethiopian Meteorological Institute for station and gridded data and the Canadian Centre for Climate Modelling and Analysis (CCCma) for CanESM2 GCM data. Special thanks are given to the editors and anonymous reviewers for constructive comments that helped improve the manuscript.

Author Contributions: Conceptualization: Mitiku A WORKU; Methodology: Mitiku A WORKU; Software: Mitiku A WORKU; Formal analysis: Mitiku A WORKU; Writing—original draft preparation: Mitiku A WORKU; Writing—review and editing: Gudina L FEYISA, Kassahun T BEKETIE, Emmanuel GARBOLINO; Resources: Mitiku A WORKU, Gudina L FEYISA, Kassahun T BEKETIE, Emmanuel GARBOLINO; Supervision: Gudina L FEYISA, Kassahun T BEKETIE.

References

Arora V K, Scinocca J F, Boer G J, et al. 2011. Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases. *Geophysical Research Letters*, 38(5): L05805, doi: 10.1029/2010GL046270.

Ayanlade A, Ojebisi S M. 2019. Climate change impacts on cattle production: analysis of cattle herders' climate variability/change adaptation strategies in Nigeria. *Change and Adaptation in Socio-Ecological Systems*, 5(1): 12–23.

Birara H, Pandey R P, Mishra S K. 2018. Trend and variability analysis of rainfall and temperature in the Tana Basin region, Ethiopia. *Journal of Water and Climate Change*, 9(3): 555–569.

Bulti D T, Abebe B G, Biru Z. 2021. Analysis of the changes in historical and future extreme precipitation under climate change in Adama city, Ethiopia. *Modeling Earth Systems and Environment*, 7(4): 2575–2587.

Deb P, Babel M S, Denis A F. 2018. Multi-GCMs approach for assessing climate change impact on water resources in Thailand. *Modeling Earth Systems and Environment*, 4(2): 825–839.

Debela N, McNeil D, Bridle K, et al. 2019. Adaptation to climate change in the pastoral and agropastoral systems of Borana, South Ethiopia: Options and barriers. *American Journal of Climate Change*, 8(1): 40–60.

Dessu S B, Melesse A M. 2013. Impact and uncertainties of climate change on the hydrology of the Mara River basin, Kenya/Tanzania. *Hydrological Processes*, 27(20): 2973–2986.

Dile Y T, Berndtsson R, Setegn S G. 2013. Hydrological response to climate change for Gilgel Abay River, in the Lake Tana Basin-Upper Blue Nile Basin of Ethiopia. *PLoS ONE*, 8(10): e79296, doi: 10.1371/journal.pone.0079296.

Fenetahun Y, Yuan Y, Xu X W, et al. 2022. Borana rangeland of southern Ethiopia: Estimating biomass production and carrying capacity using field and remote sensing data. *Plant Diversity*, 44(6): 598–606.

Gemedo D, Maass B L, Isselstein J. 2006. Rangeland condition and trend in the semiarid Borana lowlands, southern Oromia, Ethiopia. *African Journal of Range & Forage Science*, 23(1): 49–58.

Ghorbani M A, Khatibi R, Karimi V, et al. 2018. Learning from multiple models using artificial intelligence to improve model prediction accuracies: Application to river flows. *Water Resources Management*, 32(13): 4201–4215.

Goyal M K, Ojha C S P. 2012. Downscaling of surface temperature for lake catchment in an arid region in India using linear multiple regression and neural networks. *International Journal of Climatology*, 32(4): 552–566.

Gumucio T, Hansen J, Huyer S, et al. 2020. Gender-responsive rural climate services: a review of the literature. *Climate and Development*, 12: 241–254.

Habib ur Rahman M, Ahmada A, Wang X C, et al. 2018. Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan. *Agricultural and Forest Meteorology*, 253–254: 94–113.

Hashmi M Z, Shamseldin A Y, Melville B W. 2011. Statistical downscaling of watershed precipitation using gene expression programming (GEP). *Environmental Modelling & Software*, 26(12): 1639–1646.

Hassan W H, Nile B K. 2020. Climate change and predicting future temperature in Iraq using CanESM2 and HadCM3 modeling. *Modeling Earth Systems and Environment*, 7(2): 737–748.

Hassan Z, Shamsudin S, Harun S. 2014. Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature. *Theoretical and Applied Climatology*, 116: 243–257.

Hu Z Y, Hu Q, Zhang C, et al. 2016. Evaluation of reanalysis, spatially interpolated and satellite remotely sensed precipitation data sets in Central Asia. *Journal of Geophysical Research: Atmospheres*, 121(10): 5648–5663.

Hussain M, Yusof K W, Mustafa M R, et al. 2017. Projected changes in temperature and precipitation in Sarawak State of Malaysia for selected CMIP5 climate scenarios. *International Journal of Sustainable Development Planning*, 12(8): 1245–1255.

IPCC. 2013. *Climate Change 2013: The Physical Science Basis.* Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental

Panel on Climate Change. Cambridge, United Kingdom and New York, USA: Cambridge University Press.

IPCC. 2014. *Climate Change 2014: Mitigation of Climate Change*. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, USA: Cambridge University Press.

IPCC. 2022. *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK and New York, USA: Cambridge University Press.

Javaherian M, Ebrahimi H, Aminnejad B. 2021. Prediction of changes in climatic parameters using CanESM2 model based on RCP scenarios (case study): Lar dam basin. *Ain Shams Engineering Journal*, 12(1): 445-454.

Jeong D, Cannon A J, Yu B. 2022. Influences of atmospheric blocking on North American summer heatwaves in a changing climate: a comparison of two Canadian Earth system model large ensembles. *Climatic Change*, 172(1): 5, doi: 10.1007/s10584-022-03358-3.

Korecha D, Barnston A G. 2007. Predictability of June to September rainfall in Ethiopia. *Journal of American Meteorological Society*, 135(2): 628-650.

Lachgar R, Badri W, Chlaida M. 2022. Assessment of future changes in downscaled temperature and precipitation over the Casablanca-Settat region (Morocco). *Modeling Earth Systems and Environment*, 8(2): 2123-2133.

Matthew O J, Abiye O E. 2017. Evaluation of SDSM performance in simulating rainfall and temperature over Nigeria. *British Journal of Applied Science & Technology*, 20(1): 1-15.

Meinshausen M, Smith S J, Calvin K, et al. 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change*, 109: 213-241.

Mogomotsi P K, Sekelemani A, Mogomotsi G E J. 2020. Climate change adaptation strategies of small-scale farmers in Ngamiland East, Botswana. *Climatic Change*, 159(3): 441-460.

Mohammed M, Biazn B, Belete M D. 2020. Hydrological impacts of climate change in Tikur Wuha watershed, Ethiopian Rift Valley Basin. *Journal of Environment and Earth Science*, 10(2): 28-49.

Moss R H, Edmonds J A, Hibbard K A, et al. 2010. The next generation of scenarios for climate change research and assessment. *Nature*, 463: 747-756.

Mubeen M, Ahmad A, Hammad H M, et al. 2020. Evaluating the climate change impacts on water requirements of cotton-wheat in semi-arid conditions using DSSAT model. *Journal of Water and Climate Change*, 11(4): 1661-1675.

Munawar S, Rahman G, Moazzam M F U, et al. 2022. Future climate projections using SDSM and LARS-WG downscaling methods for CMIP5 GCMs over the Transboundary Jhelum River Basin of the Himalayas Region. *Atmosphere*, 13(6): 898, doi: 10.3390/atmos13060898.

Muringai R T, Naidoo D, Mafongoya P, et al. 2019. The impacts of climate change on the livelihood and food security of small-scale fishers in Lake Kariba, Zimbabwe. *Journal of Asian and African Studies*, 55(2): 298–313.

Nasim W, Belhouchette H, Tariq M, et al. 2016. Correlation studies on nitrogen for sunflower crop across the agroclimatic variability. *Environmental Science and Pollution Research*, 23(4): 3658–3670.

Ortiz-Bobea A, Ault T R, Carrillo C M, et al. 2021. Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, 11(4): 306–312.

Ozbuldu M, Irvem A. 2021. Evaluating the effect of the statistical downscaling method on monthly precipitation estimates of global climate models. *Global NEST Journal*, 23: 1–9.

Pervez S, Henebry G M. 2014. Projections of the Ganges-Brahmaputra precipitation—Downscaled from GCM predictors. *Journal of Hydrology*, 517: 120–134.

Seng C K, Weng T K, Nakayama A. 2021. Development of statistically downscaled regional climate model based on Representative Concentration Pathways for Ipoh, Subang and KLIA Sepang in Peninsular Malaysia. *IOP Conference Series: Earth and Environmental Science*, 945: 012022, doi: 10.1088/1755-1315/945/1/012022.

Shahriar S A, Siddique M A M, Rahman S M A. 2021. Climate change projection using statistical downscaling model over Chittagong Division, Bangladesh. *Meteorology and Atmospheric Physics*, 133: 1409–1427.

Sultan B, Defrance D, Iizumi T. 2019. Evidence of crop production losses in West Africa due to historical global warming in two crop models. *Scientific Reports*, 9(1): 12834, doi: 10.1038/s41598-019-49167-0.

Tekle A. 2015. Assessment of climate change impact on water availability of Bilate watershed, Ethiopian Rift Valley Basin. In: *AFRICON*. Addis Ababa, Ethiopia, 1–5, doi: 10.1109/AFRCON.2015.7332041.

van Vuuren D P, Edmonds J, Kainuma M, et al. 2011. The representative concentration pathways: an overview. *Climatic Change*, 109: 5–31.

Virgin J G, Fletcher C G, Cole J N S, et al. 2021. Cloud feedbacks from CanESM2 to CanESM5.0 and their influence on climate sensitivity. *Geoscientific Model Development*, 14(9): 5355–5372.

Wilby R L, Dawson C W, Barrow E M. 2002. SDSM—a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling &*

Software, 17(2): 145–157.

Wilby R L, Dawson C W. 2013. The statistical downscaling model: insights from one decade of application. *International Journal of Climatology*, 33(7): 1707–1719.

Worku M A, Feyisa G L, Beketie K T. 2022. Climate trend analysis for a semi-arid Borana zone in southern Ethiopia during 1981–2018. *Environmental Systems Research*, 11: 2, doi: 10.1186/s40068-022-00247-7.

Yang C L, Wang N L, Wang S J. 2017. A comparison of three predictor selection methods for statistical downscaling. *International Journal of Climatology*, 37(3): 1238–1249.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.